

**PROCEEDINGS *of the* FOURTH  
BERKELEY SYMPOSIUM ON  
MATHEMATICAL STATISTICS  
AND PROBABILITY**

*Held at the Statistical Laboratory  
University of California  
June 20–July 30, 1960,*

*with the support of*  
University of California  
National Science Foundation  
Office of Naval Research  
Office of Ordnance Research  
Air Force Office of Research  
National Institutes of Health

**VOLUME I**

**CONTRIBUTIONS TO THE THEORY OF STATISTICS**

**EDITED BY JERZY NEYMAN**

**UNIVERSITY OF CALIFORNIA PRESS  
BERKELEY AND LOS ANGELES  
1961**

# A MARTINGALE SYSTEM THEOREM AND APPLICATIONS

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## 1. Introduction

Let  $(W, \mathcal{F}, P)$  be a probability space with points  $\omega \in W$  and let  $(y_n, \mathcal{F}_n)$ ,  $n = 1, 2, \dots$ , be an *integrable stochastic sequence*:  $y_n$  is a sequence of random variables,  $\mathcal{F}_n$  is a sequence of  $\sigma$ -algebras with  $\mathcal{F}_n \subset \mathcal{F}_{n+1} \subset \mathcal{F}$ ,  $y_n$  is measurable with respect to  $\mathcal{F}_n$ , and  $E(y_n)$  exists,  $-\infty \leq E(y_n) \leq \infty$ . A random variable  $s = s(\omega)$  with positive integer values is a *sampling variable* if  $\{s \leq n\} \in \mathcal{F}_n$  and  $\{s < \infty\} = W$ . (We denote by  $\{\dots\}$  the set of all  $\omega$  satisfying the relation in braces, and understand equalities and inequalities to hold up to sets of  $P$ -measure 0.) We shall be concerned with the problem of finding, if it exists, a sampling variable  $s$  which maximizes  $E(y_s)$ .

To define a sampling variable  $s$  amounts to specifying a sequence of sets  $B_n \in \mathcal{F}_n$  such that

$$(1) \quad 0 = B_0 \subset \dots \subset B_n \subset B_{n+1} \subset \dots ; \bigcup_1^\infty B_n = W,$$

the sampling variable  $s$  being defined by

$$(2) \quad \{s \leq n\} = B_n, \quad \{s = n\} = B_n - B_{n-1}.$$

We shall be particularly interested in the case in which the sequence  $(y_n, \mathcal{F}_n)$  is such that the sequence of sets

$$(3) \quad B_n = \{E(y_{n+1}|\mathcal{F}_n) \leq y_n\}$$

satisfies (1). We shall call this the *monotone case*. In this case a sampling variable  $s$  is defined by

$$(4) \quad \{s \leq n\} = \{E(y_{n+1}|\mathcal{F}_n) \leq y_n\},$$

and  $s$  satisfies

$$(5) \quad E(y_{n+1}|\mathcal{F}_n) \begin{cases} > y_n, & s > n, \\ \leqq y_n, & s \leq n. \end{cases}$$

The relations (5) will be fundamental in what follows.

This research was sponsored in part by the Office of Naval Research under Contract No. Nonr-226 (59), Project No. 042-205.

In the monotone case we have for the sampling variable  $s$  defined by (4) the following characterization:

$$(6) \quad s = \text{least positive integer } j \text{ such that } E(y_{j+1}|\mathcal{F}_j) \leq y_j.$$

Now even in the nonmonotone case we can always define a random variable  $s$  by (6), setting  $s = \infty$  if there is no such  $j$ ; let us call it the *conservative* random variable. The following statement is evident: the necessary and sufficient condition that there exists a sampling variable  $s$  satisfying (5) is that we are in the monotone case, and in this case  $s$  is the conservative random variable.

In section 3 we are going to show that *in the monotone case, under certain regularity assumptions, the conservative sampling variable  $s$  maximizes  $E(y_s)$ .*

## 2. An example

Before proceeding with the general theory we shall give a simple and instructive example of the monotone case in the form of a *sequential decision problem*.

Let  $x, x_1, x_2, \dots$  be a sequence of independent and identically distributed random variables with  $E(x^+) < \infty$ , where we denote  $a^+ = \max(a, 0)$ ,  $a^- = \max(-a, 0)$ . We observe the sequence  $x_1, x_2, \dots$  sequentially and can stop with any  $n \geq 1$ . If we stop with  $x_n$  we receive the reward  $m_n = \max(x_1, \dots, x_n)$ , but the cost of taking the observations  $x_1, \dots, x_n$  is some strictly increasing function  $g(n) \geq 0$ , so that our net gain in stopping with  $x_n$  is  $y_n = m_n - g(n)$ . The decision whether to stop with  $x_n$  or to take the next observation  $x_{n+1}$  must be a function of  $x_1, \dots, x_n$  alone. *Problem:* what stopping rule maximizes the expected value  $E(y_s)$ , where  $s$  is the random sample size defined by the stopping rule? We assume that the distribution function  $F(u) = P\{x \leq u\}$  is known. That  $E(y_n)$  exists follows from the inequality

$$(7) \quad y_n^+ \leq x_1^+ + \dots + x_n^+,$$

which implies that  $E(y_n^+) < \infty$ .

Let  $\mathcal{F}_n$  be the  $\sigma$ -algebra generated by  $x_1, \dots, x_n$ . Then  $(y_n, \mathcal{F}_n)$  is an integrable stochastic sequence, and we have

$$(8) \quad \begin{aligned} E(y_{n+1}|\mathcal{F}_n) - y_n &= \int [m_{n+1} - m_n] dF(x_{n+1}) - [g(n+1) - g(n)] \\ &= \int (x - m_n)^+ dF(x) - f(n), \end{aligned}$$

where we have set

$$(9) \quad f(n) = g(n+1) - g(n) = \text{cost of taking the } (n+1)\text{st observation.}$$

Since we have assumed  $g(n)$  to be strictly increasing, and  $f(n) > 0$ , it is easily seen that there exist unique constants  $\alpha_n$  such that

$$(10) \quad \int (x - \alpha_n)^+ dF(x) = f(n), \quad n \geq 1.$$

By (8) and (10),

$$(11) \quad E(y_{n+1}|\mathcal{F}_n) \begin{cases} > y_n & \text{if } m_n < \alpha_n, \\ \leq y_n & \text{if } m_n \geq \alpha_n. \end{cases}$$

The conservative random variable  $s$  defined by (6) is therefore

$$(12) \quad s = \text{least positive integer } j \text{ such that } m_j \geq \alpha_j.$$

We are in the monotone case if and only if this  $s$  is a sampling variable and for every  $n$

$$(13) \quad \{E(y_{n+1}|\mathcal{F}_n) \leq y_n\} \subset \{E(y_{n+2}|\mathcal{F}_{n+1}) \leq y_{n+1}\},$$

that is,  $m_n \geq \alpha_n$  implies  $m_{n+1} \geq \alpha_{n+1}$ , which will certainly be the case, since  $m_n \leq m_{n+1}$ , if  $\alpha_n \geq \alpha_{n+1}$ , that is, if  $f(n)$  is nondecreasing and hence  $\alpha_n$  is non-increasing. We shall henceforth assume this to hold. We shall now show that in this case the conservative random variable  $s$  is in fact a sampling variable, that is, that  $P\{s < \infty\} = 1$ . We have

$$(14) \quad \{s > n\} = \{m_n < \alpha_n\},$$

and hence

$$(15) \quad P\{s < \infty\} = 1 - \lim_n P\{s > n\} = 1 - \lim_n P\{m_n < \alpha_n\} \\ \geq 1 - \lim_n P\{m_n < \alpha_1\} = 1 - \lim_n P^n\{x < \alpha_1\} = 1,$$

since by hypothesis  $f(1) > 0$  so that by (10),  $P\{x < \alpha_1\} < 1$ . In fact, for any  $r \geq 0$ ,

$$(16) \quad E(s^r) = \sum_{n=1}^{\infty} n^r P\{s = n\} \leq \sum_{n=1}^{\infty} n^r P\{s > n - 1\} \\ \leq 1 + \sum_{n=2}^{\infty} n^r P\{m_{n-1} < \alpha_1\} \\ = 1 + \sum_{n=2}^{\infty} n^r P^{n-1}\{x < \alpha_1\} < \infty,$$

so that  $s$  has finite moments of all orders.

It is of interest to consider the special case  $g(n) = cn$ ,  $0 < c < \infty$ . Here  $f(n) = c$  and  $\alpha_n = \alpha$ , where  $\alpha$  is defined by

$$(17) \quad \int (x - \alpha)^+ dF(x) = c,$$

and  $s$  is the first  $j \geq 1$  for which  $x_j \geq \alpha$ . Hence

$$\begin{aligned}
 P\{s = j\} &= P\{x \geq \alpha\} P^{j-1}\{x < \alpha\}, \\
 E(s) &= \frac{1}{P\{x \geq \alpha\}}, \\
 (18) \quad E(y_s) &= \sum_{j=1}^{\infty} P\{s = j\} E(m_j - cj | s = j), \\
 E(m_j | s = j) &= E(x_j | x_1 < \alpha, \dots, x_{j-1} < \alpha, x_j \geq \alpha) \\
 &= \frac{1}{P\{x \geq \alpha\}} \int_{\{x \geq \alpha\}} x dF(x),
 \end{aligned}$$

so that

$$\begin{aligned}
 (19) \quad E(y_s) &= \frac{1}{P\{x \geq \alpha\}} \left[ \int_{\{x \geq \alpha\}} x dF(x) - c \right] \\
 &= \frac{1}{P\{x \geq \alpha\}} \left[ \int (x - \alpha)^+ dF(x) - c + \alpha P\{x \geq \alpha\} \right] = \alpha,
 \end{aligned}$$

an elegant relation.

### 3. General theorems

In the following three lemmas we assume that  $(y_n, \mathcal{F}_n)$  is any integrable stochastic sequence and that  $s$  and  $t$  are any sampling variables such that  $E(y_s)$  and  $E(y_t)$  exist.

LEMMA 1. *If for each  $n$ ,*

$$(20) \quad E(y_s | \mathcal{F}_n) \geq y_n \quad \text{if } s > n,$$

*and*

$$(21) \quad E(y_t | \mathcal{F}_n) \leq y_n \quad \text{if } s = n, t > n,$$

*then*

$$(22) \quad E(y_s) \geq E(y_t).$$

*Conversely, if  $E(y_s)$  is finite and (22) holds for every  $t$ , then (20) and (21) hold for every  $t$ .*

PROOF.

$$\begin{aligned}
 (23) \quad E(y_s) &= \sum_{n=1}^{\infty} \int_{\{s=n, t \leq n\}} y_s dP + \sum_{n=1}^{\infty} \int_{\{s=n, t > n\}} y_n dP \\
 &= \sum_{n=1}^{\infty} \int_{\{s \geq n, t=n\}} y_s dP + \sum_{n=1}^{\infty} \int_{\{s=n, t>n\}} y_n dP \\
 &\geq \sum_{n=1}^{\infty} \int_{\{s \geq n, t=n\}} y_n dP + \sum_{n=1}^{\infty} \int_{\{s=n, t>n\}} y_t dP \\
 &= E(y_t).
 \end{aligned}$$

To prove the converse, for a fixed  $n$  let

$$(24) \quad V = \{s > n \text{ and } E(y_s|\mathcal{F}_n) < y_n\};$$

then  $V \in \mathcal{F}_n$ . Define

$$(25) \quad t' = \begin{cases} s, & \omega \notin V, \\ n, & \omega \in V. \end{cases}$$

Then  $t'$  is a sampling variable. Since  $E(y_s)$  is finite, by (22)  $E(y_n) < \infty$  and then  $E(y_{t'})$  exists. But

$$\begin{aligned} (26) \quad E(y_{t'}) &= \int_{\{t'=s\}} y_{t'} dP + \int_V y_{t'} dP = \int_{\{t'=s\}} y_s dP + \int_V y_n dP \\ &\geq \int_{\{t'=s\}} y_s dP + \int_V y_s dP = E(y_s). \end{aligned}$$

But by (22),  $E(y_{t'}) \leq E(y_s)$ . Hence

$$(27) \quad \int_V y_n dP = \int_V y_s dP$$

and therefore  $P(V) = 0$ , which proves (20). To prove (21) let

$$(28) \quad V = \{s = n, t > n, \text{ and } E(y_t|\mathcal{F}_n) > y_n\},$$

and define

$$(29) \quad t' = \begin{cases} s, & \omega \notin V, \\ t, & \omega \in V. \end{cases}$$

Then

$$\begin{aligned} (30) \quad E(y_{t'}) &= \int_{\{t'=s\}} y_{t'} dP + \int_V y_{t'} dP = \int_{\{t'=s\}} y_s dP + \int_V y_t dP \\ &\geq \int_{\{t'=s\}} y_s dP + \int_V y_n dP = \int_{\{t'=s\}} y_s dP + \int_V y_s dP = E(y_s), \end{aligned}$$

and again  $P(V) = 0$ , which proves (21).

**LEMMA 2.** *If for each  $n$ ,*

$$(31) \quad E(y_{n+1}|\mathcal{F}_n) \geq y_n, \quad s > n,$$

*and if*

$$(32) \quad \liminf_n \int_{\{s>n\}} y_n^+ dP = 0,$$

*then for each  $n$ ,*

$$(33) \quad E(y_s|\mathcal{F}_n) \geq y_n, \quad s \geq n.$$

PROOF. (compare [2], p. 310). Let  $V \in \mathfrak{F}_n$  and  $U = V\{s \geq n\}$ .

Then

$$\begin{aligned}
 (34) \quad \int_U y_n dP &= \int_{V\{s=n\}} y_n dP + \int_{V\{s>n\}} y_n dP \\
 &\leqq \int_{V\{s=n\}} y_n dP + \int_{V\{s>n\}} y_{n+1} dP \\
 &= \int_{V\{n \leq s \leq n+1\}} y_s dP + \int_{V\{s>n+1\}} y_{n+1} dP \\
 &\leqq \cdots \leqq \int_{V\{n \leq s \leq n+r\}} y_s dP + \int_{V\{s>n+r\}} y_{n+r} dP \\
 &\leqq \int_{V\{n \leq s \leq n+r\}} y_s dP + \int_{\{s>n+r\}} y_{n+r}^+ dP.
 \end{aligned}$$

Therefore

$$(35) \quad \int_U y_n dP \leqq \int_{V\{s \geq n\}} y_s dP + \liminf_n \int_{\{s>n\}} y_n^+ dP = \int_U y_s dP,$$

which is equivalent to (33).

LEMMA 3. If for each  $n$ ,

$$(36) \quad E(y_{n+1} | \mathfrak{F}_n) \leqq y_n, \quad s \leqq n,$$

and if

$$(37) \quad \liminf_n \int_{\{t>n\}} y_n^- dP = 0,$$

then

$$(38) \quad E(y_t | \mathfrak{F}_n) \leqq y_n, \quad s = n, \quad t \geq n.$$

PROOF. Let  $V \in \mathfrak{F}_n$  and  $U = V\{s = n, t \geq n\}$ . Then

$$\begin{aligned}
 (39) \quad \int_U y_n dP &= \int_{V\{s=n, t=n\}} y_n dP + \int_{V\{s=n, t>n\}} y_n dP \\
 &\geqq \int_{V\{s=n, t=n\}} y_n dP + \int_{V\{s=n, t>n\}} y_{n+1} dP \\
 &= \int_{V\{s=n, n \leq t \leq n+1\}} y_t dP + \int_{V\{s=n, t>n+1\}} y_{n+1} dP \\
 &\geqq \cdots \geqq \int_{V\{s=n, n \leq t \leq n+r\}} y_t dP + \int_{V\{s=n, t>n+r\}} y_{n+r} dP \\
 &\geqq \int_{V\{s=n, n \leq t \leq n+r\}} y_t dP - \int_{\{t>n+r\}} y_{n+r}^- dP.
 \end{aligned}$$

Therefore

$$(40) \quad \int_U y_n dP \geq \int_{V\{s=n, t \geq n\}} y_t dP - \liminf_n \int_{\{t > n\}} y_n^- dP = \int_U y_t dP,$$

which is equivalent to (38).

We can now state the main result of the present paper.

**THEOREM 1.** *Let  $(y_n, \mathcal{F}_n)$  be an integrable stochastic sequence in the monotone case and let  $s$  be the conservative sampling variable*

$$(41) \quad s = \text{least positive integer } j \text{ such that } E(y_{j+1} | \mathcal{F}_j) \leqq y_j.$$

*Suppose that  $E(y_s)$  exists and that*

$$(42) \quad \liminf_n \int_{\{s > n\}} y_n^+ dP = 0.$$

*If  $t$  is any sampling variable such that  $E(y_t)$  exists and*

$$(43) \quad \liminf_n \int_{\{t > n\}} y_n^- dP = 0,$$

*then*

$$(44) \quad E(y_s) \geqq E(y_t).$$

**PROOF.** From lemmas 1, 2, and 3 and relations (5).

We shall now establish a lemma (see [2], p. 303) which provides sufficient conditions for (42) and (43).

**LEMMA 4.** *Let  $(y_n, \mathcal{F}_n)$  be a stochastic sequence such that  $E(y_n^+) < \infty$  for each  $n \geq 1$ , and let  $s$  be any sampling variable. If there exists a nonnegative random variable  $u$  such that*

$$(45) \quad E(su) < \infty,$$

*and if*

$$(46) \quad E[(y_{n+1} - y_n)^+ | \mathcal{F}_n] \leqq u, \quad s > n,$$

*, then*

$$(47) \quad E(y_s^+) < \infty, \quad \lim_n \int_{\{s > n\}} y_n^+ dP = 0.$$

**PROOF.** Define

$$(48) \quad z_1 = y_1^+, \quad z_{n+1} = (y_{n+1} - y_n)^+ \quad \text{for } n \geq 1, \quad w_n = z_1 + \cdots + z_n.$$

Then

$$(49) \quad y_n^+ \leqq w_n$$

(and hence  $y_n^+ \leqq w_s$  if  $s \geq n$ ), and by (46)

$$(50) \quad E(z_{n+1} | \mathcal{F}_n) \leqq u, \quad s > n.$$

Hence

$$\begin{aligned}
 (51) \quad E(y_s^+) &\leq E(w_s) = \sum_{n=1}^{\infty} \int_{\{s=n\}} w_n dP = \sum_{n=1}^{\infty} \sum_{j=1}^n \int_{\{s=n\}} z_j dP \\
 &= \sum_{j=1}^{\infty} \sum_{n=j}^{\infty} \int_{\{s=n\}} z_j dP = \sum_{j=1}^{\infty} \int_{\{s>j-1\}} z_j dP \\
 &= E(y_1^+) + \sum_{j=2}^{\infty} \int_{\{s>j-1\}} E(z_j | \mathcal{F}_{j-1}) dP \\
 &\leq E(y_1^+) + \sum_{j=2}^{\infty} \int_{\{s>j-1\}} u dP = E(y_1^+) + \sum_{j=2}^{\infty} \sum_{n=j}^{\infty} \int_{\{s=n\}} u dP \\
 &= E(y_1^+) + \sum_{n=2}^{\infty} \int_{\{s=n\}} (n-1)u dP = E(y_1^+) + E(su) - E(u) \\
 &\leq E(y_1^+) + E(su) < \infty,
 \end{aligned}$$

and hence from (49)

$$(52) \quad \lim_n \int_{\{s>n\}} y_n^+ dP \leq \lim_n \int_{\{s>n\}} w_s dP = 0.$$

**REMARK.** Lemma 4 remains valid if we replace  $a^+$  by  $a^-$  or by  $|a|$  throughout.

#### 4. Application to the sequential decision problem of section 2

Recalling the problem of section 2, let  $x, x_1, x_2, \dots$  be independent and identically distributed random variables with  $E(x^+) < \infty$ ,  $\mathcal{F}_n$  the  $\sigma$ -algebra generated by  $x_1, \dots, x_n$ ,  $g(n) \geq 0$ ,  $f(n) = g(n+1) - g(n) > 0$  and nondecreasing,  $m_n = \max(x_1, \dots, x_n)$ , and  $y_n = m_n - g(n)$ . The constants  $\alpha_n$  are defined by

$$(53) \quad E[(x - \alpha_n)^+] = f(n)$$

and are nonincreasing; we are in the monotone case, and the conservative sampling variable  $s$  is the first  $j \geq 1$  such that  $m_j \geq \alpha_j$ ; thus

$$(54) \quad \{s > n\} = \{m_n < \alpha_n\}.$$

We have shown in section 2 that

$$(55) \quad P\{s < \infty\} = 1, \quad E(s^r) < \infty \quad \text{for } r \geq 0.$$

We wish to apply theorem 1. As concerns  $s$  it will suffice to show that  $E(y_s^+) < \infty$  and that

$$(56) \quad \lim_n \int_{\{s>n\}} y_n^+ dP = 0,$$

which we shall do by using lemma 4. Let

$$(57) \quad Y_n = m_n^+ - g(n).$$

Then

$$(58) \quad Y_n^+ = y_n^+, \quad E(Y_n^+) = E(y_n^+) \leq E(x_1^+ + \cdots + x_n^+) = nE(x^+) < \infty,$$

and

$$\begin{aligned} (59) \quad E[(Y_{n+1} - Y_n)^+ | \mathcal{F}_n] &= E\{[m_{n+1}^+ - m_n^+ - f(n)]^+ | \mathcal{F}_n\} \\ &\leq E[(m_{n+1}^+ - m_n^+) | \mathcal{F}_n] \leq E(x_{n+1}^+ | \mathcal{F}_n) \\ &= E(x^+) < \infty. \end{aligned}$$

Hence by lemma 4, setting  $u = E(x^+)$ ,

$$(60) \quad E(y_s^+) = E(Y_s^+) < \infty$$

and

$$(61) \quad \lim_n \int_{\{s > n\}} y_n^+ dP = \lim_n \int_{\{s > n\}} Y_n^+ dP = 0,$$

which were to be proved.

To establish the conditions on  $t$  of theorem 1 we assume that  $E x^- < \infty$ ; then since  $y_n^- \leq x_1^- + g(n)$  it follows that  $E(y_n^-) < \infty$ . Define a random variable  $u$  by setting

$$(62) \quad u(\omega) = f(n) \quad \text{if} \quad t(\omega) = n.$$

Since

$$(63) \quad (y_{n+1} - y_n)^- \leq f(n)$$

and  $f(n)$  is nondecreasing, it follows that

$$(64) \quad E[(y_{n+1} - y_n)^- | \mathcal{F}_n] \leq u \quad \text{if} \quad t \geq n.$$

We now assume that  $f(n) \leq h(n)$ , where  $h(n)$  is a polynomial of degree  $r \geq 0$ , and that  $E(t^{r+1}) < \infty$ . Then

$$(65) \quad E(tu) = \sum_{n=1}^{\infty} \int_{\{t=n\}} nf(n) dP \leq \sum_{n=1}^{\infty} nh(n) P\{t=n\}.$$

Since

$$(66) \quad E(t^{r+1}) = \sum_{n=1}^{\infty} n^{r+1} P\{t=n\} < \infty,$$

it follows that  $E(tu) < \infty$ . Then by the remark following lemma 4,

$$(67) \quad E(y_t^-) < \infty \quad \text{and} \quad \lim_n \int_{\{t>n\}} y_n^- dP = 0,$$

and all the conditions of theorem 1 are established. Thus we have proved

**THEOREM 2.** Suppose that  $E|x| < \infty$  and that in addition to the conditions on  $g(n)$  in the first paragraph of this section we have  $f(n) \leq h(n)$ , where  $h(n)$  is a polynomial of degree  $r \geq 0$ . If  $t$  is any sampling variable for which  $E(t^{r+1}) < \infty$  then  $-\infty < E(y_t) \leq E(y_s) < \infty$ , where  $s$  is the conservative sampling variable defined by (54).

If  $g(n) = nc$  then  $f(n) = c$  and we can take  $r = 0$ . Hence

**COROLLARY 1.** *If  $E|x| < \infty$  and  $y_n = m_n - cn$ ,  $0 < c < \infty$ , then if  $t$  is any sampling variable for which  $E(t) < \infty$ ,  $E(y_t) \leq E(y_s) = \alpha$  [see (19)], where  $\alpha$  is defined by  $E(x - \alpha)^+ = c$  and  $s =$  the first  $j \geq 1$  such that  $x_j \geq \alpha$ . Thus  $s$  is optimal in the class of all sampling variables with finite expectations.*

To replace the condition  $E(t^{r+1}) < \infty$  in theorem 2 and corollary 1 by conditions on  $y_t$  we require the following theorem which is of interest in itself. We omit the proof.

**THEOREM 3.** *Let  $F(u)$  be a distribution function. Define  $G(u) = \prod_{n=1}^{\infty} F(u + n)$ . Then  $G(u)$  is a distribution function if and only if*

$$(68) \quad \int_0^{\infty} u dF(u) < \infty,$$

and for any integer  $b \geq 1$ ,

$$(69) \quad \int_0^{\infty} u^b dG(u) < \infty$$

if and only if

$$(70) \quad \int_0^{\infty} u^{b+1} dF(u) < \infty.$$

**COROLLARY 2.** *If  $y_n = m_n - cn$ ,  $0 < c < \infty$ , and  $b$  is any integer  $\geq 1$ , then*

$$(71) \quad E(\sup_{n \geq 1} y_n^+)^b < \infty$$

if and only if

$$(72) \quad E(x^+)^{b+1} < \infty.$$

**PROOF.** We can assume  $c = 1$ . Define

$$(73) \quad G(u) = P\{\sup_{n \geq 1} y_n^+ \leq u\}.$$

Then for  $u \geq 0$ ,

$$(74) \quad \begin{aligned} G(u) &= P\{x_1 \leq u + 1, x_2 \leq u + 2, \dots, x_n \leq u + n, \dots\} \\ &= \prod_{n=1}^{\infty} F(u + n). \end{aligned}$$

By theorem 3,

$$(75) \quad E(\sup_{n \geq 1} y_n^+)^b = \int_0^{\infty} u^b dG(u) < \infty$$

if and only if

$$(76) \quad \int_0^{\infty} u^{b+1} dF(u) = E(x^+)^{b+1} < \infty.$$

**THEOREM 4.** *Assume  $E|x| < \infty$ ,  $E(x^+)^2 < \infty$ . If  $y_n = m_n - g(n)$  where  $g(n)$  is a polynomial of degree  $r \geq 1$  such that*

$$(77) \quad g(1) > 0,$$

$g(n+1) - g(n)$  is positive and nondecreasing, then for any sampling variable  $t$ ,

$$(78) \quad E(y_t) \leq E(y_s),$$

where  $s$  is the conservative sampling variable defined by (54).

PROOF. By theorem 2, if  $E(t^*) < \infty$  then (78) holds. Hence we can assume that  $E(t^*) = \infty$ . Now

$$\begin{aligned} (79) \quad g(1) &> 0, & f(1) &= g(2) - g(1) > 0, \\ g(2) &\geq g(1) + f(1), & g(3) - g(2) &\geq f(1), \\ g(3) &\geq g(1) + 2f(1), \\ &\dots\dots \\ g(n) &\geq g(1) + (n-1)f(1). \end{aligned}$$

Let

$$(80) \quad a = \frac{1}{2} \min [g(1), f(1)] > 0.$$

Then by (79),

$$(81) \quad g(n) \geq an \quad \text{for } n \geq 1.$$

Let

$$(82) \quad \tilde{y}_n = m_n - \frac{a}{2} n.$$

By corollary 2,  $E(\tilde{y}_t^+) < \infty$ . Then since

$$(83) \quad y_t = \tilde{y}_t + \frac{a}{2} t - g(t) \leq \tilde{y}_t^+ - \frac{1}{2} g(t)$$

we have

$$(84) \quad E(y_t) \leq E(\tilde{y}_t^+) - \frac{1}{2} E[g(t)] = -\infty,$$

so that (78) holds in this case too.

REMARK. If in the case  $g(n) = cn$  we define  $\bar{y}_n = x_n - cn$ , then

$$(85) \quad \bar{y}_n \leq y_n, \quad \bar{y}_s = y_s.$$

Hence for any sampling variable  $t$ ,

$$(86) \quad E(\bar{y}_t) \leq E(y_t) \leq E(y_s) = E(\bar{y}_s),$$

so that  $s$  is also optimal for the stochastic sequence  $(\bar{y}_n, \mathcal{F}_n)$ .

## 5. A result of Snell

As an application of lemmas 1 and 2, we are going to obtain Snell's result on sequential game theory [3].

LEMMA 5 (Snell). Let  $(y_n, \mathcal{F}_n)$  be a stochastic sequence satisfying  $y_n \geq u$  for

each  $n$  with  $E|u| < \infty$ . Then there exists a semimartingale  $(x_n, \mathcal{F}_n)$  such that for every sampling variable  $t$  and every  $n$ ,

$$(87) \quad E(x_t | \mathcal{F}_n) \geq x_n \quad \text{if } t \geq n, \quad x_n \geq E(u | \mathcal{F}_n),$$

$$(88) \quad x_n = \min [y_n, E(x_{n+1} | \mathcal{F}_n)],$$

and

$$(89) \quad \liminf x_n = \liminf y_n.$$

We will assume the validity of this lemma, and prove the following theorem by applying lemmas 1 and 2.

**THEOREM 5 (Snell).** Let  $(y_n, \mathcal{F}_n)$  and  $(x_n, \mathcal{F}_n)$  satisfy the conditions of lemma 5. For  $\epsilon \geq 0$  define  $s = j$  to be the first  $j \geq 1$  such that  $x_j \geq y_j - \epsilon$ . If  $\epsilon > 0$ , then

$$(90) \quad E(y_s) \leq E(y_t) + \epsilon$$

for every sampling variable  $t$ . If  $\epsilon = 0$  and if  $P\{s < \infty\} = 1$ , then (90) still holds.

**PROOF.** It is obvious that in both cases  $s$  is a sampling variable. We need to verify that  $P\{s < \infty\} = 1$ . If  $\epsilon > 0$ , by (89) this is true.

Since  $(x_n, \mathcal{F}_n)$  is a semimartingale,

$$(91) \quad E(x_{n+1} | \mathcal{F}_n) \geq x_n.$$

By (88) and the definition of  $s$ ,

$$(92) \quad E(x_{n+1} | \mathcal{F}_n) = x_n \quad \text{for } s > n.$$

Since  $-x_n \leq E(-u | \mathcal{F}_n)$  and  $E|u| < \infty$ , by lemma 2 and (92), we have

$$(93) \quad E(x_s | \mathcal{F}_n) \leq x_n \quad \text{for } s > n.$$

By (87), (93), and lemma 1, we obtain  $E(x_s) \leq E(x_t)$ , and therefore, by definition of  $s$ ,

$$(94) \quad E(y_s) \leq E(x_s) + \epsilon \leq E(x_t) + \epsilon \leq E(y_t) + \epsilon.$$

Thus the proof is complete.

J. MacQueen and R. G. Miller, Jr., in a recent paper [1], treat the problem of section 2 by completely different methods. Reference should also be made to a paper by C. Derman and J. Sacks [4], in which the formulation and results are very similar to those of the present paper.

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